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EXPECTED VERSUS REALIZED INCOME CHANGES: A TEST OF THE RATIONAL EXPECTATIONS HYPOTHESIS

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Expected versus Realized Income Changes: A Test of the Rational Expectations Hypothesis [1]

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Abstract

We analyze answers to household survey questions on whether the respondents' household income has changed in the past twelve months, and on whether the respondents expect their household income to change in the next twelve months. Both questions are answered on a discrete five points scale. The data are an unbalanced panel of eleven consecutive annual waves.

Using cross-tabulations of expected and realized changes, we first test the "best-case" hypothesis. This hypothesis implies, under two different nonparametric assumptions on how respondents form their predictions, that respondents have rational expectations, that there are no common unexpected shocks, and that reported expectations are best predictions of future outcomes. We find that the best case hypothesis is rejected: for all years, too many respondents who predict an income fall, *ex post* report that their household income has not changed.

We then construct a bivariate ordered probit random effects panel data model, in which we explain both expectations and realizations from background variables such as age, education level, and labour market status, and from the one year lagged expectation and realization. We show that the hypothesis of rational expectations implies certain restrictions on the parameters in the two equations of this model. The model is estimated by simulated maximum likelihood using the Geweke-Hajivassilou-Keane (GHK) method. The hypothesis of rational expectations is rejected. The hypotheses that expectations are adaptive or naive can be tested in a similar way, and are also rejected.

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1 Introduction

How economic agents form their expectations is an important issue in many fields of economic theory. Common assumptions in the theoretical literature are rational expectations, adaptive expectations, or naive expectations. Empirical evidence on whether these theories provide a realistic description of actual behaviour, is less common. The most direct approach to this is to use survey information on what agents expect, and compare that with *ex post* realizations. Several studies have analyzed the issue using micro data from business surveys on whether output is expected to increase, decrease or remain the same in the next three months. The answers are then compared with the answers to a similar question asked three months later on what has actually happened to output. Using a latent variable model, Ivaldi (1992) finds that the hypothesis of rational expectations (REH) is not always rejected for the French manufacturing industry. Nerlove and Schuermann (1995, 1997), on the other hand, using different latent variable models, unambiguously reject REH for Swiss and UK firms. They also reject the hypotheses of adaptive expectations (AEH) and naive expectations (NEH).

Empirical work on expectations of private households or individuals, is even more scarce. Still, expectations of future incomes, prices, and labour market opportunities, play a major role in many life cycle models, in which households optimize some discounted value of utility in the current and in future periods. Expectations are thus important in dynamic structural models of savings, portfolio choice, consumption, investments in durable goods, labour supply, job search, fertility, etc. In most such models, REH or another hypothesis like AEH or NEH, are taken for granted. The fit of the model or significance of certain behavioral parameters are sometimes used as indirect evidence in favour or against one of these hypotheses, but this evidence is not very strong. If the wrong hypothesis is used, this may hamper the usefulness of the structural models for policy analysis.

It is therefore important to investigate in a more direct way how private households or individuals form their expectations. The way to do this is to use survey questions on the household's future expectations on relevant economic phenomena, like prices and household income. Various household surveys contain questions on the levels or changes of these variables expected by the respondents, and respondents' uncertainty in these predictions. Some studies using Italian and Dutch surveys have investigated whether the answers to such questions are related to the respondents' actual economic behaviour in a way that theory would predict. For example, Guiso, Japelli and Terlizzese (1996) show that income uncertainty has a negative impact on the household portfolio share of risky assets in Italy. Hochguertel (1998) finds a similar result for the Netherlands. On the other hand, Alessie and Lusardi (1997) do not find the expected negative relationship between savings and the predicted income change in data for the Netherlands.

In this paper, we focus on household income expectations. We will not look at the impact of expectations on economic behaviour like savings, portfolio choice, etc., but will focus on a direct analysis of expectations formation, by comparing expected and realized income changes. Our analysis is in line with the studies of Das, Dominitz and van Soest (1999) and Das and van Soest (1997, 1999). We use panel data on Dutch households covering the years 1984 until 1994. In each wave before 1994, heads of households have answered questions on whether the respondents' household income has changed in the past twelve months, and on whether they expect their household income to change in the next twelve months.[1] Both questions are answered on a discrete five points scale.

First, we present the data, and apply the method of Das, Dominitz and van Soest (1999). Using cross-tabulations of expected and realized changes, we nonparametrically test the "best-case" hypothesis, implying that respondents have rational expectations, that there are no common unexpected shocks, and that reported expectations are best predictions of future outcomes, under two different nonparametric assumptions on how respondents form their predictions. We find that the best case hypothesis is rejected: for all years, too many respondents who predict an income fall, report *ex post* that their

[1] Since 1994 respondents were only asked about their realized income change in the past twelve months.

household income has not changed. This shows that people either do not have rational expectations, or are faced with positive macroeconomic shocks for a number of consecutive years. The latter explanation becomes less plausible the more panel waves are used.

The next step is to find out for which groups of households REH cannot be confirmed, and to analyze how people form their expectations if they do not use rational expectations. Das and van Soest (1997, 1999) have used univariate models for the deviations between observed answers on expected and realized changes. Their approach, however, does not account for the conceptual difference between expectations and realizations questions: the former reflects some location measure (e.g. mean, mode, or median) of the respondent's subjective distribution of the income change, the latter is one draw from the actual income change distribution. Even if actual and subjective distribution coincide, the discrete nature of both variables implies that expectations and realizations are not necessarily the same. This is shown by Manski (1990) and taken into account by the nonparametric tests.

The main contribution of the current paper is that we set up and estimate a structural framework that takes the Manski (1990) critique into account. Observed categorical realizations and expectations are modeled as two separate ordered response variables. We introduce a bivariate ordered probit random effects panel data model, in which we explain both expectations and realizations from background variables such as age, education level, and labour market status, and from the one year lagged expectation and realization. Under the assumption that respondents' expectations reflect the mean or median of their subjective income change distribution, we derive restrictions on the parameters in the two equations of this model which are valid under the null hypothesis of rational expectations. These restrictions can be tested.

The model extends the models used by Nerlove and Schuermann (1995, 1997) in various ways. It allows for background variables and lagged dependent variables. Moreover, the model describes the complete eleven waves panel, while Nerlove and Schuermann look at one pair of consecutive waves at the time. As a consequence, our model is not only useful to test whether REH is valid on average, for the population as a whole, but can also be used to analyze how deviations between predictions and realizations vary with household characteristics. Finally, while Nerlove and Schuermann cannot address the issue of macroeconomic shocks and test REH under the assumption that macroeconomic shocks do not play a role, we can distinguish macroeconomic shocks from violations of REH under the maintained assumption that macroeconomic shocks are not correlated to background characteristics.

The model is estimated by simulated maximum likelihood using the Geweke-Hajivassilou-Keane (GHK) algorithm. The main conclusion is that the hypothesis of rational expectations is rejected. In particular, high educated and disabled heads of household seem to be too pessimistic, on average. The hypotheses that expectations are adaptive or naive can be tested in a similar way, and are also rejected.

The structure of the remainder of this paper is as follows. In Section 2 we briefly describe the data. In Section 3, we discuss the nonparametric tests of Das, Dominitz and van Soest (1999). In Section 4, we present the bivariate model for expectations and realizations, and explain how REH, AEH and NEH can be tested in this framework. In Section 5, we discuss the results. Section 6 concludes.

2 Data

The data we use in the analysis are taken from the Dutch Socio-Economic Panel (SEP), which is administered by Statistics Netherlands. This panel runs since April 1984. Until 1989 households were interviewed twice a year: in April and in October. Since 1990, information is gathered in May only.

We focus on subjective questions concerning household income growth. These questions are:

1: Did your household's income increase, decrease, or remain unchanged during the past twelve months?
Possible answers: strong decrease (1); decrease (2); no change (3); increase (4); strong increase (5).

2: What will happen to your household's income in the next twelve months?
Possible answers: see 1.

To get the smoothest possible transition from the change in the timing of the interviews, we use the April waves from 1984 till 1989, and the May waves from 1990 onwards (till 1994). A disadvantage of using the April waves is that we cannot use information on actual income. Between 1984 and 1989, information on monthly income is collected in all the October waves but not in all April waves. Moreover, in 1990 the questions concerning income from several main sources such as earnings changed completely, so that comparable data on actual income for the whole time period of eleven years are not available. We will not use actual income variables, and will use variables like education level and age to proxy the actual income level.

The SEP is an unbalanced panel. Each year households leave the panel, and new households enter. The numbers of (heads of) households for all waves are presented in Table 1. From the 1994 wave, we only use the answer to the question concerning the past income change. We removed some households from the sample because of missing answers to the subjective questions concerning income change, or because information on household characteristics or characteristics of the head of household was missing. Table 1 displays the numbers of removed observations. The 1990 wave has substantial item non-response on the subjective income change questions. An explanation is that the questions in this wave are asked to either the head of household or the partner. In all other waves, the answers were given by both the head of household and the partner. The rather high number of observations which are removed because of missing characteristics in 1991, is mainly due to lack of information on the education level.

In the model which will be introduced in Section 4, we will use the pooled data set for all waves. This pooled data set is an unbalanced panel which originally contains 9691 observations. However, since we will only use observations that remain in the panel for at least three consecutive years, the number of observations drops to 6408.[2] Slightly less than half of these are present in more than five waves; 603 households are observed in all eleven waves. The final row of Table 1 presents the actual number of observations per wave that is used in the estimation of the model. Obviously, new households that have entered the panel in the final years are not included, since they are not observed for at least three consecutive waves. This explains why the number of observations declines towards the end of the sample period.

In the remainder of the paper, we will assume that sample selection, item nonresponse on the income change variables, and attrition, are random conditional on the background characteristics included in the regressions. The small nonresponse rates on the income change variables (except for the 1990 wave, where nonresponse is due to the construction of the questionnaire) gives some confidence that this assumption is reasonable.

Table 1. Number of observations per wave.

	wave										
	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
number of households:	3980	3458	4692	4611	5036	5119	5212	4821	5347	5184	5187
removed because of:											
1) item nonresponse on subjective income change questions:	144	91	177	138	145	154	1875	35	61	41	235
2) missing characteristics:	35	35	97	100	306	73	9	591	37	31	-
used for estimation in pooled data set:	2369	2558	3753	3844	4051	4110	3008	3085	3529	3298	3045

[2] There were 1981 households with complete information for only one wave and 1302 households with information in only two waves.

3 Nonparametric tests

In this section we apply the method of Das, Dominitz and van Soest (1999) to compare predictions and outcomes. Section 3.1 briefly summarizes the framework and presents the bounds on features of the empirical distribution of realized outcomes under the best case scenario hypothesis, which implies REH. In Section 3.2 we present the results. While Das et al. used the October waves of 1984 till 1989, we will use the April waves of 1984 till 1989 and the May waves of 1990 till 1994.

3.1 Method

Loosely stated, REH means that predictions and outcomes are based upon the same distribution. Manski (1990) develops a framework in which REH can be tested, provided several additional assumptions are made and maintained (including the assumption that there are no macro-economic shocks). He refers to the complete set of assumptions as the "best case scenario." He shows that the best case scenario leads to bounds on the conditional outcome probabilities given the predictions. Das et al. (1999) extend Manski's framework to the ordered response case with more than two categories. It turns out that, in the case with more than two categories, the bounds depend on the assumption on how respondents form their "best prediction." Here, we discuss the bounds in case of the modal and the median category assumption. Das et al. (1999) also discuss the "category containing the mean assumption," but this can only be used if exact quantitative data on realized income changes are available, which is not the case for the used waves of the SEP in the current paper (see Section 2).

The "best case scenario," i.e., the null hypothesis which will be tested, involves more than just REH. It is the joint hypothesis that: 1) respondents have rational expectations, i.e. their subjective income change distribution coincides with the actual distribution from which the realized income change is drawn; 2) different households are independent observations, implying that there are no macroeconomic shocks; 3) a given respondent uses the same income concept and the same category bounds for the answers on predicted and realized income change (different respondents may use different concepts or bounds); and 4) the respondents' predicted income changes reflect the modal category or the median category of their subjective income distribution. Rejecting the null hypothesis can therefore be interpreted as rejecting REH if the other three assumptions are maintained.

Modal category assumption

If each respondent's prediction is the category with the highest probability, Das et al. (1999) show that the best case scenario implies the following bounds on the conditional probabilities of the (categorical) realization r given the (categorical) prediction p.

$$\mathrm{P}\{r = k|p = k\} \geq \mathrm{P}\{r = j|p = k\}, \quad j = 1, \ldots, K, \tag{1}$$

where K is the total number of (ordered) categories ($K = 5$, in our case). The inequality can be tested for each $j \neq k$; it can be tested for the sample as a whole, or for specific subgroups. We perform the test separately for each pair of consecutive waves.

The test based on the modal category assumption does not make use of the ordered nature of the categorical data. The same inequalities have also been used for testing REH on the basis of business surveys, without explicitly discussing the framework. Ivaldi (1992) refers to it as a weak, nonparametric, test of REH.

Median category assumption

This assumption is equivalent to the assumption that respondents predict the category containing the median of their subjective income distribution. It explicitly makes use of the fact that the response categories are ordered. Das et al. (1999) derive the following bounds on the conditional probabilities under the best case scenario.

$$\mathrm{P}\{r > k|p = k\} \leq \frac{1}{2} \tag{2}$$

and

$$\mathrm{P}\{r < k|p = k\} \leq \frac{1}{2}. \tag{3}$$

The inequalities under both the modal and the median category assumption can be tested using the asymptotic distribution of the sample fractions which are the sample analogues of the population fractions in the inequalities. This distribution is only valid if the observed realized income changes are independent, which explains why the null hypothesis must include the assumption that there are no common shocks.

3.2 Results of the nonparametric tests

Table 2 presents the estimates of the conditional probabilities of the realizations given the predictions for the sample as a whole. These estimates are used to test for significant violations of the modal category assumption, i.e. of one of the inequalities in (1). For $k = 1$ (strong decrease predicted), the inequality (1) is not satisfied for 1986-1987, 1988-1989, and 1989-1990. Only for 1986-1987, the violation is significant. For $k = 2$, the test results are unanimous: for all pairs of waves, the estimate of $P\{r = 3|p = 2\}$ significantly exceeds the estimate of $P\{r = 2|p = 2\}$, implying that the null hypothesis is rejected. For $k > 2$, no significant violations of (1) are found. Thus the conclusion of Das et al. (1999) is confirmed for this longer time span: in all years, too many of those who expect their incomes to fall, *ex post* report no change. The long time span for which this is the case, makes it implausible that this is due to macroeconomic shocks; macroeconomic shocks will sometimes be positive and sometimes be negative, and the probability that ten consecutive shocks are positive is quite small. Thus the result suggests that at least some respondents do not have rational expectations.

Table 2. Estimates of $P\{r = j|p = k\}$ (in percentages), where p stands for *predicted* category and r for *realized* category of future income change ($n = \#\{i : p_i = k\}$).

		$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	n
$k = 1$: strong decrease	'84 - '85	36.3	28.8	25.9	7.6	1.4	212
	'85 - '86	41.2	21.7	22.7	10.3	4.1	97
	'86 - '87	25.8	16.7	43.9	9.1	4.6	66
	'87 - '88	36.8	19.1	30.9	8.8	4.4	68
	'88 - '89	32.5	15.6	35.1	10.4	6.5	77
	'89 - '90	22.9	28.6	28.6	14.3	5.7	35
	'90 - '91	41.5	19.5	19.5	12.2	7.3	41
	'91 - '92	39.7	18.0	20.5	18.0	3.9	78
	'92 - '93	45.6	21.5	19.0	10.1	3.8	79
	'93 - '94	46.4	17.5	23.7	9.3	3.1	97
$k = 2$: decrease	'84 - '85	14.2	26.7	45.2	11.3	2.7	1237
	'85 - '86	6.9	19.9	55.1	16.0	2.1	682
	'86 - '87	10.0	20.1	54.7	13.2	2.1	583
	'87 - '88	12.0	22.8	52.1	10.7	2.4	457
	'88 - '89	11.2	20.8	50.1	14.3	3.6	475
	'89 - '90	11.7	20.0	33.2	27.9	7.2	265
	'90 - '91	16.8	23.3	36.2	16.4	7.3	232
	'91 - '92	17.2	22.3	41.1	15.5	3.9	489
	'92 - '93	12.8	23.9	42.2	17.3	3.9	510
	'93 - '94	14.9	27.6	40.2	14.7	2.6	619
$k = 3$: no change	'84 - '85	4.9	14.5	58.0	19.0	3.6	1350
	'85 - '86	2.8	8.7	60.4	24.3	3.8	1676
	'86 - '87	2.9	9.3	64.8	19.7	3.2	2747
	'87 - '88	2.3	8.3	67.0	19.2	3.2	3009
	'88 - '89	2.1	5.7	61.9	26.4	4.1	3065
	'89 - '90	2.6	6.6	45.7	37.8	7.2	2112
	'90 - '91	3.8	9.2	53.5	26.6	7.0	1915
	'91 - '92	4.6	9.9	53.3	27.7	4.6	2460
	'92 - '93	4.5	10.2	55.8	26.2	3.4	2730
	'93 - '94	3.8	11.7	59.5	22.3	2.7	2829

continued on next page

Table 2, continued							
$k = 4$: increase	'84 - '85	3.4	8.3	37.5	38.8	12.0	291
	'85 - '86	4.0	3.7	30.5	49.2	12.6	374
	'86 - '87	1.9	4.8	34.6	43.1	15.7	703
	'87 - '88	1.8	4.6	35.3	44.6	13.7	762
	'88 - '89	2.3	4.0	24.3	52.9	16.6	832
	'89 - '90	2.0	4.1	14.8	55.7	23.4	560
	'90 - '91	3.4	4.4	23.6	46.3	22.3	681
	'91 - '92	3.9	8.3	24.3	46.3	17.1	1196
	'92 - '93	2.6	6.9	27.3	50.6	12.6	1250
	'93 - '94	3.5	8.1	29.0	49.2	10.3	984
$k = 5$: strong increase	'84 - '85	0.0	9.1	45.5	36.4	9.1	11
	'85 - '86	6.7	13.3	20.0	13.3	46.7	15
	'86 - '87	10.3	0.0	13.8	44.8	31.0	29
	'87 - '88	2.2	6.7	22.2	31.1	37.8	45
	'88 - '89	2.6	2.6	13.2	21.1	60.5	38
	'89 - '90	0.0	0.0	15.4	26.9	57.7	26
	'90 - '91	0.0	5.9	17.7	26.5	50.0	34
	'91 - '92	6.1	3.7	19.5	35.4	35.4	82
	'92 - '93	5.9	3.4	12.5	27.3	51.1	88
	'93 - '94	10.5	14.9	11.9	25.4	37.3	67

Table 3 shows 90% confidence intervals for the cumulative probabilities that can be used to test the best case scenario under the median category assumption. For $k = 1$, inequality (2) is significantly violated in 7 combinations of years. For $k = 2$, inequality (2) is violated in all combinations of years. For $k = 3$ and $k = 4$, no violations of either (2) or (3) are found. For $k = 5$, we find that (3) is rejected in 5 out of 10 combinations of years, suggesting that too many of those who predict a large income increase, report a smaller increase or no increase at all. Together with the result for $k = 1$, this suggests that too many people give predictions in the extreme categories. That we find this with the median category assumption only is explained by the fact that the modal category assumption always requires a plurality of probability mass in the predicted category, whereas the median category requires a majority when either the lowest or highest category is predicted. For $k = 2$, however, the results of median and modal category are completely in line with each other: the best case scenario is rejected for all combinations of years.

Table 3. 90% confidence intervals for the (cumulative) probabilities where p stands for *predicted* category and r for *realized* category of future income change (in percentages; $n = \#\{i : p_i = k\}$)

		$P\{r < k \mid p = k\}$		$P\{r > k \mid p = k\}$		n
		lower	upper	lower	upper	
$k = 1$: strong decrease	'84 - '85	–	–	58.2	69.1	212
	'85 - '86	–	–	50.5	67.0	97
	'86 - '87	–	–	65.4	83.1	66
	'87 - '88	–	–	56.3	72.9	68
	'88 - '89	–	–	58.8	76.3	77
	'89 - '90	–	–	65.5	88.8	35
	'90 - '91	–	–	45.9	71.2	41
	'91 - '92	–	–	51.1	69.4	78
	'92 - '93	–	–	45.2	63.6	79
	'93 - '94	–	–	45.3	61.9	97
$k = 2$: decrease	'84 - '85	12.5	15.8	56.9	61.5	1237
	'85 - '86	5.3	8.5	70.4	76.0	682
	'86 - '87	7.9	12.0	66.9	73.1	583
	'87 - '88	9.5	14.5	61.5	68.9	457
	'88 - '89	8.8	13.5	64.5	71.5	475
	'89 - '90	8.5	14.9	63.6	73.0	265
	'90 - '91	12.8	20.8	54.6	65.2	232
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	'92 - '93	10.3	15.2	59.8	66.8	510
	'93 - '94	12.5	17.2	54.2	60.8	619
$k = 3$: no change	'84 - '85	17.6	21.2	20.7	24.5	1350
	'85 - '86	10.2	12.7	26.4	30.0	1676
	'86 - '87	11.2	13.3	21.7	24.3	2747
	'87 - '88	9.6	11.5	21.2	23.7	3009
	'88 - '89	6.9	8.5	29.0	31.8	3065
	'89 - '90	8.2	10.3	43.3	46.9	2112
	'90 - '91	11.7	14.2	31.8	35.4	1915
	'91 - '92	13.3	15.6	30.7	33.8	2460
	'92 - '93	13.5	15.8	28.2	31.0	2730
	'93 - '94	14.3	16.6	23.7	26.4	2829

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Table 3, continued						
$k = 4$:	'84 - '85	44.3	54.0	8.9	15.2	291
increase	'85 - '86	34.1	42.4	9.7	15.4	374
	'86 - '87	38.2	44.3	13.4	17.9	703
	'87 - '88	38.8	44.7	11.6	15.7	762
	'88 - '89	27.9	33.2	14.5	18.7	832
	'89 - '90	18.1	23.7	20.5	26.3	560
	'90 - '91	28.5	34.4	19.7	24.9	681
	'91 - '92	34.2	38.8	15.3	18.9	1196
	'92 - '93	34.5	39.0	11.1	14.2	1250
	'93 - '94	38.0	43.1	8.7	11.9	984
$k = 5$:	'84 - '85	76.7	100.0	–	–	11
strong increase	'85 - '86	32.1	74.5	–	–	15
	'86 - '87	54.8	83.1	–	–	29
	'87 - '88	50.3	74.1	–	–	45
	'88 - '89	26.4	52.5	–	–	38
	'89 - '90	26.4	58.2	–	–	26
	'90 - '91	35.9	64.1	–	–	34
	'91 - '92	55.9	73.3	–	–	82
	'92 - '93	40.1	57.6	–	–	88
	'93 - '94	53.0	72.4	–	–	67

4 Model

The results in the previous section imply that the joint hypothesis of no macro-economic shocks, rational expectations, and questions on expected and realized income changes are answered in the same way, is rejected for all time periods we consider. In this section we will impose more structure and formulate an econometric model to investigate why this joint hypothesis is rejected. Can we reject rational expectations, and, if so, can we indicate which groups of people typically have non-rational expectations, or can we explain the results from macroeconomic shocks and do we not need to reject REH? We introduce a bivariate model explaining the answers to the predicted as well as the realized income change questions, which generalizes the models used by Nerlove and Schuermann (1995, 1997).

Realized income changes

We allow for an unbalanced panel, but will only use respondents i who participate in at least three consecutive waves. N_i is defined as the number of consecutive waves in which respondent i is observed and index t corresponds to the different waves (ranging from -1 to $N_i - 2$, where the wave with index -1 is used for the explanatory variables in the initial condition equation; see below.).

The answer to the realized income change question given in wave t of the survey by respondent i is denoted by y_{it}. This is an ordered variable, with five possible answers coded from 1 (strong decrease) to 5 (strong increase). Like in a standard ordered response model, we assume that it relates to an underlying continuous latent variable y^*_{it} as follows:

$$y_{it} = j \text{ if } m^y_{j-1} < y^*_{it} \leq m^y_j \;\; (j = 1, \ldots, 5).$$

The category boundaries $-\infty = m^y_0 < m^y_1 < \ldots < m^y_4 < m^y_5 = \infty$ are assumed to be constant across individuals and across time; m^y_1, m^y_2, m^y_3 and m^y_4 are parameters to be estimated. [3]

The underlying latent variable is modelled using the following dynamic random effects panel data equation.

$$y^*_{it} = X'_{i,t-1}\beta_1 + \rho y^*_{i,t-1} + \lambda_t + \alpha_{iy} + \epsilon_{it}, \tag{4}$$

where $X_{i,t-1}$ is a vector of background variables reflecting, for example, age, education level, and labour market status of the respondent. Note that y^*_{it} refers to income in the period between times $t-1$ and t, and $X_{i,t-1}$ refers to the beginning of this period. This explains why $X_{i,t-1}$ is included rather than X_{it}. An additional reason for this is that it will make comparing the equations for predictions and realizations easier, as will be explained below. Note that we have included the latent lagged variable $y^*_{i,t-1}$ and not the latent observed variable $y_{i,t-1}$. This reflects the notion that the observed variable is discrete due to the way it is measured only, while the underlying continuous latent variable is the

[3] Some of them will be normalized; see below.

magnitude of economic relevance. The parameter α_{iy} is an individual specific (random) effect, included to allow for unobserved heterogeneity across respondents; ϵ_{it} is an error term. Assumptions on the distributions of α_{iy} and ϵ_{it} will be given below. Time dummies λ_t are included to allow for macro-economic shocks. These macro-economic shocks are thus assumed to be common for all respondents, and do not vary with $X_{i,t-1}$ or $y^*_{i,t-1}$.

Since the equation contains the lagged income change, it cannot be used for $t = 0$. Due to the latent variable nature of the model, simply ignoring $t = 0$ leads to inconsistent estimates (see Heckman, 1981a). Following Heckman (1981b), we solve this problem by adding a linearized reduced form static equation for y^*_{i0}:

$$y^*_{i0} = X'_{i,-1}\beta_0 + \epsilon_{i0},$$

where the individual effect is included in the error term ϵ_{i0}. The presence of $X_{i,-1}$ in the above equation explains why we can only use observations who are present in at least three consecutive waves. Only from the third wave onwards ($t = 1$), the observations provide useful information for estimating the parameters in the dynamic equation. [4]

Predictions of income changes

The answer to the expected income change question given in wave t of the survey by respondent i is denoted by p_{it}. This is an ordered response variable. Analogously to y_{it}, we model it using an underlying continuous latent variable p^*_{it}:

$$p_{it} = j \text{ if } m^p_{j-1} < p^*_{it} \leq m^p_j \ \ (j = 1, \ldots, 5).$$

We make the same assumptions on the category boundaries m^p_j as on m^y_j. It seems natural that m^y_j and m^p_j are identical, but, apart from some necessary normalization to identify the model (see below), this is something we can test, and we will not impose it *a priori*.

We specify the following latent variable equation for p^*_{it}:

[4] Some (but probably very little) efficiency could be gained by using the observations which are in the panel for two waves, since these do provide information for estimating the auxiliary parameters in the reduced form equation. Moreover, an alternative which avoids the loss of the first observation ($t = -1$) would be to include $X_{i,0}$ instead of $X_{i,-1}$ in the equation for $t = 0$. This would drive a larger wedge between static reduced form and dynamic equations, however.

$$p_{it}^* = X_{it}'\gamma_1 + \theta_1 y_{it}^* + \theta_2 p_{i,t-1}^* + \nu_t + \alpha_{ip} + \omega_{it}. \tag{5}$$

The parameter α_{ip} is an individual specific (random) effect, included to allow for unobserved heterogeneity across respondents. This will probably be correlated with α_{iy}. ω_{it} is an error term. Time dummies ν_t in this equation are included to allow for anticipated macroeconomic effects.

The income change prediction p_{it}^* given in wave t refers to the income change in the next twelve months. It is allowed to depend on the realized income change y_{it}^* which the respondent has experienced during the past twelve months. p_{it}^* is a prediction of $y_{i,t+1}^*$, so the effect of y_{it} on p_{it} may reflect a genuine economic process which leads to correlation between y_{it}^* and $y_{i,t+1}^*$. It may also, however, reflect a psychological effect of past income changes on future expectations. The two can be disentangled using (4), the equation for y_{it}^*. The parameter ρ in (4) is the genuine effect, a deviation between ρ and θ_1 would indicate a psychological effect. This effect will not be there if REH is satisfied. This example therefore already illustrates how the two equations (4) and (5) can and will be used to test for (parameter restrictions implied by) rational expectations.

Finally, we also allow the prediction in year t to depend on the prediction in year $t-1$. Such a relation might be interpreted in an adaptive expectations framework, as we will show below. Earlier work on a univariate model suggested that such an effect is significant though quantitatively not very important (see Das and van Soest, 1999).

For the same reason as in the case of the realized income change, a separate linearized reduced form equation is used for the prediction in the first time period:

$$p_{i0}^* = X_{i0}'\gamma_0 + \theta_0 y_{i0}^* + \omega_{i0}.$$

Distributional assumptions

We assume that the error terms $\{(\epsilon_{it}, \omega_{it}), t = 0, ..., N_i - 2\}$ are normally distributed and independent of the regressors $\{X_{it}, t = -1, ..., N_i - 2\}$ and of the individual effects α_{iy} and

α_{ip}. We allow for arbitrary correlations between ϵ_{it}, ω_{it}, $\epsilon_{i,t-1}$, and $\omega_{i,t-1}$, but we assume independence between error terms in waves t and s if $|t-s|>1$.

The individual effects $(\alpha_{iy}, \alpha_{ip})$ are treated as random effects, assumed to be independent of X_{it}. Fixed effects models are not considered. First, many of the regressors of interest such as age and education level variables do not vary over time or vary over time in a systematic way, and their effects would not be identified in a fixed effects context. Second, due to the discrete bivariate nature of the model, estimation techniques allowing for fixed effects are, to our knowledge, not available. Third and most importantly, systematic time persistent violations of REH would be captured in the fixed effects. If, for example, for some group of respondents the individual effects in the realizations equation would be much larger than those in the predictions equation, this would imply that this group systematically underestimates their income changes and does not have rational expectations. Treating the individual effects as fixed and eliminating them from the model, would hide this type of REH violations and would reduce the power of the test for REH in the direction of time persistent non-rational behaviour. Using random effects, assuming individual effects are independent of background variables, avoids this problem.

We allow for correlation between α_{iy} and α_{ip}. More specifically, we assume that $(\alpha_{iy}, \alpha_{ip})$ is bivariate normal with mean zero, variances $\sigma^2_{\alpha_y}$ and $\sigma^2_{\alpha_p}$, and covariance $\sigma_{\alpha_y,\alpha_p}$.

Rational expectations

In the model introduced above, the relation between predictions and realizations is very flexible. We will now show that rational expectations implies testable restrictions on the parameters in the two dynamic equations.

We assume that the predictions p^*_{it} reflect some location measure of the individual's subjective distribution of the underlying continuous income change variable y^*_{it}, conditional on the individual's information set at time $t-1$. Since our (normality) assumptions imply that the conditional distribution of y^*_{it} is symmetric, the conditional mean and the conditional median of y^*_{it} are the same, so it does not make any difference which of the two location measures we use. The assumption that p^*_{it} reflects the median of the conditional distribution of y^*_{it} is in line with the median category assumption in the previous section, since the median category is the same as the category containing the median of the underlying continuous latent variable. It is not in line with the modal category assumption, since the modal category is not necessarily the category containing the mode of the continuous variable.

Rational expectations implies that the realized income change $y^*_{i,t+1}$ is drawn from this same distribution. If the respondent's information set at the time of the interview in wave t is denoted by I_{it}, and if the location measure used by the respondent is the conditional mean, we get

$$p^*_{it} = E\{y^*_{i,t+1}|I_{it}\}.$$

Since the respondent's information set will contain the lagged variables and the exogenous variables X_{it}, this implies

$$X'_{it}\gamma_1 + \theta_1 y^*_{it} + \theta_2 p^*_{i,t-1} + \nu_t + \alpha_{ip} + \omega_{it} = X'_{i,t}\beta_1 + \rho y^*_{i,t} + \alpha_{iy} + E\{\lambda_{t+1} + \epsilon_{i,t+1}|I_{it}\}.$$

A necessary condition for this to hold for all respondents in all time periods is

$$\gamma_1 = \beta_1; \;\; \theta_1 = \rho; \;\; \theta_2 = 0. \tag{6}$$

If we would have used the median instead of the mean, the result would have been the same, the only difference being that $E_t\{\lambda_{t+1}+\epsilon_{i,t+1}|I_{it}\}$ would be replaced by $Median_t\{\lambda_{t+1}+\epsilon_{i,t+1}|I_{it}\}$.

Rational expectations thus implies the equality restrictions on the parameters in the two dynamic equations given in (6). We will estimate the model with and without imposing these restrictions. A likelihood ratio test will then show whether the hypothesis of rational expectations can be rejected or not.[5]

[5] In principle, a similar set of restrictions could be tested for the static equations for $t = 0$. Since these are considered as auxiliary equations, however, we chose not to consider such restrictions.

The restrictions to be tested do not involve the time dummies ν_t and λ_{t+1}. The reason is that REH implies $\nu_t = E\{\lambda_{t+1}|I_{it}\}$ or $\nu_t = Median\{\lambda_{t+1}|I_{it}\}$, but not $\nu_t = \lambda_{t+1}$. Without imposing REH or other additional assumptions, we cannot consistently estimate $E\{\lambda_{t+1}|I_{it}\}$ or $Median\{\lambda_{t+1}|I_{it}\}$; we can only estimate λ_{t+1} itself. On the other hand, if we do impose REH, we can interpret the estimates of ν_t in the restricted model (imposing (6)) as estimates of $E\{\lambda_{t+1}|I_{it}\}$ or $Median\{\lambda_{t+1}|I_{it}\}$. The differences between the estimates of the realized macroeconomic effects λ_{t+1} and the estimates of the anticipated macroeconomic effects ν_t can then be interpreted as estimates of the realizations of unanticipated macroeconomic effects, i.e., as macroeconomic shocks.

The test for REH thus allows for unanticipated macroeconomic effects, and is in this sense more general than the tests used by Nerlove and Schuermann (1995, 1997). On the other hand, the restrictions in (6) clearly rely on the assumption that macro-economic effects are uncorrelated with the right hand side variables $X_{i,t}$, $y^*_{i,t}$ and $p^*_{i,t-1}$. This maintained assumption can be relaxed by testing fewer restrictions. For example, a test on $\theta_1 = \rho$ and $\theta_2 = 0$ can be seen as a test of REH allowing for macro-economic shocks which can be correlated with $X_{i,t-1}$ but conditional on $X_{i,t-1}$ not with $y^*_{i,t-1}$ or $p^*_{i,t-1}$. Perhaps the weakest test is a simple test on whether θ_2 is nonzero, since there does not seem any reason why macro-economic shocks should be correlated to past predictions, conditional on everything else. As we will see later, a significant value of θ_2 can (partly) be motivated from the assumption of adaptive expectations.

Normalization

The issue of normalization slightly complicates comparing the restricted model (imposing (6)) and the unrestricted model. In the unrestricted model, we need separate scale and location normalizations for the latent variables reflecting expected and realized incomes. This is achieved through the category thresholds: $m_2^y = m_2^p = -1$, and $m_3^y = m_3^p = 1$. In the restricted model, the equality of slope coefficients in the two dynamic equations implies that the scale normalization needs to be imposed in one of the two equations only; the scale of the other equation is then identified due to the restrictions. (The location normalization remains the same as in the unrestricted model, since we do not restrict the time dummies.) Thus in the restricted model, we impose $m_2^y = -1$, $m_3^y = 1$ and $m_2^p = -1$, but we estimate m_3^p. This implies that the number of degrees of freedom for the likelihood ratio test is reduced by 1.[6]

Adaptive and Naive Expectations

Although this is probably less relevant than REH, the framework can also be used to test the hypotheses of adaptive expectations (AEH) and naive expectations (NEH). These cases are nested in the general two equations model. AEH implies (see Nerlove and Schuermann, 1995, equation (2.8)):

$$p_{it}^* - p_{i,t-1}^* = \delta[y_{it}^* - p_{i,t-1}^*] + u_t$$

for some parameter $\delta > 0$, where u_t is an anticipated macroeconomic effect. This implies the following restrictions on the parameters of the two dynamic equations:

$$\gamma_1 = 0; \quad \theta_1 + \theta_2 = 1. \tag{7}$$

Naive expectations would imply that the (latent) prediction is given by the current realization (see Nerlove and Schuermann, 1995, equation (2.9)):

$$p_{it}^* = y_{it}^* + u_t.$$

This is the special case of AEH with $\delta = 1$, and thus implies the following restrictions on the parameters of the general model:

$$\gamma_1 = 0; \quad \theta_1 = 1; \quad \theta_2 = 0. \tag{8}$$

[6] Using a different normalization would avoid this problem, but would not make the estimation results more transparent.

Like REH, both AEH and NEH can be tested using likelihood ratio tests or Wald tests on parameter restrictions in the general two equations model.

It could also be the case that expectations are driven by a mixture of AEH and REH. In our framework, it is possible to test the hypothesis that expectations are a convex combinations of REH and AEH expectations:

$$p_{it}^* = \alpha E\{y_{i,t+1}^* | I_{it}\} + (1-\alpha)\{\delta y_{it}^* + (1-\delta)p_{i,t-1}^* + u_t\}$$

for some $\alpha \in [0,1]$. Eliminating α en δ, it is straightforward to show that this implies the following non-linear set of parameter restrictions.

$$(1-\rho)\gamma_1 \;=\; (1-\theta_1-\theta_2)\beta_1. \tag{9}$$

These restrictions can again be tested using a likelihood ratio test. (The normalization issue is similar to that in the REH test, and can be accounted for in the same way.)

Estimation

The complete bivariate model for all waves is a recursive system of ordered response equations. Due to the normality assumptions on the error terms and the random individual effects, the likelihood contribution of one respondent can be written as a multivariate normal probability, with covariance matrix depending on the parameters. Exact computation of the likelihood would require high dimensional numerical integration and is therefore infeasible in practice. This is a typical case for smooth simulated maximum likelihood, where the exact likelihood contributions are replaced by approximations based upon a number (R, say) of independent random draws for each individual. See Hajivassiliou and Ruud (1994), for example. If R tends to infinity, the approximating likelihood tends to the exact likelihood, and the estimates based upon maximizing the approximate likelihood will be similar to the maximum likelihood estimates. Under appropriate regularity conditions, if draws are independent across individuals, and if R tends to infinity faster than $\sqrt{n}$, the simulated maximum likelihood estimator and the exact maximum likelihood estimator are asymptotically equivalent, and standard errors etc. can be computed in the same way as for the exact ML–estimator.

The remaining issue is how to do the draws and how to use them to approximate the likelihood. The crude frequency simulator – based upon full draws of all the errors, yielding a zero or a one for each replication – is intuitively attractive, but leads to an approximation of the likelihood which is non-differentiable with respect to the parameters of the model, making it hard to find the maximum. A much better alternative here is the GHK (Geweke, Hajivassiliou and Keane) simulator, which is specifically designed for multivariate normal probabilities, and which has been applied successfully to similar models. See Hajivassiliou and Ruud (1994) or Keane (1993) for a description and further references. The idea is that the multivariate probability in the likelihood is written recursively as a product of univariate conditional normal probabilities, where the conditions are inequalities. Independent draws from the uniform distribution on [0,1] are then recursively transformed into draws from a truncated normal, where truncation is based upon the same inequality conditions. The conditional probabilities given the inequalities are then replaced by the conditional probabilities given the previous draws. The latter are univariate normal probabilities and therefore easy to work with. The likelihood contribution is approximated by an average over R approximations based upon R such sequences of draws. The approximate likelihood is a differentiable function of the parameters, and the regularity conditions needed for asymptotic equivalence of exact ML and simulated ML will be satisfied (provided that R tends to infinity faster than $\sqrt{n}$).

The results we present are based upon $R = 25$. We also estimated the model with $R = 10$, which gave similar results. This suggests that 25 replications is enough in our application.

5 Results

Table 4 presents the estimation results of the parameters in the dynamic equations (4) and (5) in the unrestricted model. [7] The first part of the table refers to the realization y^* and the second part corresponds to the prediction p^*. All but one of the slope coefficients in the equation for y^* (β_1) and all but three of the slope coefficients in the equation for p^* (γ_1) are significant at the 5% level. The signs of the coefficients in γ_1 and β_1 are always the same.

A female head of household (*gender=2*), on average, predicts and experiences a lower income change than a male head of household (*gender=1*), *ceteris paribus.* Realized and predicted income changes are, on average, lower when the head of household is older. The results for the dummies for education level are as expected. On average, those with higher equation level predict and experience higher changes in income. [8] This is in line with the stylized fact that life cycle income patterns are steeper for the higher educated. The effect of education level on the predictions seems smaller than the effect on the realizations. The dummies referring to the labor market status indicate that unemployed and disabled heads of households experience and predict lower income growth than others (working heads). Similarly, income changes for two earner households are lower than for one earner households.

Considering the parameters that reflect the dynamics of the model we see that past actual income growth positively relates to current actual income growth. Still, since ρ is only 0.43 and thus far less than one, the effect of changes in income in the past on current income growth vanishes quite rapidly. The estimates of θ_1 and θ_2 indicate that current realized income growth and past predictions have a positive impact on predicted income growth in the next twelve months. The effect of past predictions (θ_2) is significant at the

[7] See Table A1 in the appendix for the definitions of the exogenous variables. Estimation results for the parameters in the auxiliary initial condition equations are presented in Table A2 in the appendix.

[8] For the predicted income change the coefficient for education level 4 is slightly higher than for education level 5, but this difference is far from significant.

10% level but not at the 5% level. The effect of the past realization is stronger, though not as strong as in the equation for the realization.

Table 4. Estimates of the parameters in the unrestricted model

Realization(y)			Prediction (p)		
variable	estimate	t-value	variable	estimate	t-value
gender	-0.16	-7.14	gender	-0.11	-4.66
age/10	-0.24	-6.53	age/10	-0.30	-7.75
$(\text{age}/10)^2$	0.015	3.85	$(\text{age}/10)^2$	0.021	5.41
d_edu2	0.017	0.62	d_edu2	0.020	0.74
d_edu3	0.069	2.74	d_edu3	0.060	2.41
d_edu4	0.21	6.70	d_edu4	0.085	2.50
d_edu5	0.26	6.69	d_edu5	0.081	1.89
d_unem	-0.14	-3.05	d_unem	-0.19	-5.00
d_ret	-0.093	-2.48	d_ret	-0.034	-1.02
d_dis	-0.097	-2.69	d_dis	-0.22	-6.48
d_two	-0.091	-4.89	d_two	-0.060	-3.41
ρ	0.43	16.38	θ_1	0.31	3.33
			θ_2	0.15	1.77
λ_{1986}	1.25	12.48	ν_{1986}	0.98	7.90
λ_{1987}	1.13	10.98	ν_{1987}	1.02	8.34
λ_{1988}	1.09	10.66	ν_{1988}	1.06	8.85
λ_{1989}	1.36	13.09	ν_{1989}	1.05	7.97
λ_{1990}	1.62	15.30	ν_{1990}	1.01	6.82
λ_{1991}	1.17	10.85	ν_{1991}	1.13	8.52
λ_{1992}	1.16	11.03	ν_{1992}	1.12	8.82
λ_{1993}	1.19	11.46	ν_{1993}	0.94	7.59
λ_{1994}	0.98	9.52			
m_1^y	-1.86	-122.13	m_1^p	-2.02	108.37
m_2^y	-1		m_2^p	-1	
m_3^y	1		m_3^p	1	
m_4^y	2.62	141.30	m_4^p	2.58	107.85
σ_ϵ	1.32	100.89	σ_ω	0.91	30.03
σ_{α_y}	0.065	2.34	σ_{α_p}	0.19	7.62
$\sigma_{\alpha_y,\alpha_p}$	0.0017	0.33			
$\sigma_{\epsilon_t,\omega_t}$	-0.34	-2.63			
$\sigma_{\epsilon_t,\omega_{t-1}}$	0.37	7.96			
$\sigma_{\epsilon_t,\epsilon_{t-1}}$	-0.46	-10.86			
$\sigma_{\omega_t,\omega_{t-1}}$	-0.084	-1.78			
$\sigma_{\omega_t,\epsilon_{t-1}}$	-0.039	-2.50			
log likelihood: -59404 (number of observations = 6408)					

The estimated covariance structure of the random effects and the error terms is largely in line with what we would expect. The variance of the prediction errors (σ_ω^2) is smaller than the variance of the error terms in the realizations (σ_ϵ^2), in line with the fact that the prediction is a location measure of the (subjective) income distribution, while the realization is one draw of the (actual) income change distribution. The negative correlation between $\epsilon_{i,t-1}$ and $\epsilon_{i,t}$ can be due to the transitory component of the income level, which induce a negative correlation between income changes. The negative correlation between $\epsilon_{i,t}$ (referring to the income change between $t-1$ and t) and $\omega_{i,t}$ (referring to the predicted change between t and $t+1$) then shows that respondent are aware of this.

The estimated variance of the individual effect in the predictions is larger than that in the realizations, indicating larger unobserved heterogeneity in the subjective than in the objective variable. The two individual effects have a significant positive correlation of about 0.14, which is insignificant and surprisingly small: we would expect that most of the individual effect in the realization were in the respondent's information set, so that it could be used to predict the future income change.

Testing the Rational Expectations Hypothesis

Rational expectations implies the parameter restrictions in the dynamic equations given in (6). We re-estimated the model under these restrictions and used a likelihood ratio test to test them. Estimation results for the restricted model are presented in Table A3 in the appendix. The realization of the likelihood ratio test statistic is equal to 49.8, by far exceeding the critical value of $\chi^2_{12;0.05} = 21.0$. We therefore conclude that REH is rejected.

Comparing the parameters in the equations for realized and predicted income growth gives us an indication of why REH is rejected. Table 5 gives the estimates and t-values of the differences between β_1 and γ_1, ρ and θ_1, and θ_2 and 0 in the unrestricted model, and thus gives insight in the separate REH restrictions in (6). We see that all differences are insignificant at the two-sided 5% level except those related to education level and the dummy for disability of the head of household. For example, we cannot reject the hypothesis that past income growth influences realized and predicted income growth in the next twelve months in the same way: the difference between the estimates of the coefficients of the lagged income change (ρ and θ_1) is not significant.

Table 5. Estimates of the differences between β_1 and γ_1 and ρ and θ_1.

$\beta_1 - \gamma_1$:	estimate	t-value
gender	-0.052	-1.60
age/10	0.060	1.15
$(\text{age}/10)^2$	-0.0056	-1.05
d_edu2	-0.0021	-0.057
d_edu3	0.0091	0.26
d_edu4	0.12	2.68
d_edu5	0.18	3.09
d_unem	0.052	0.96
d_ret	-0.059	-1.25
d_dis	0.12	2.52
d_two	-0.031	-1.22
$\rho - \theta_1$	0.12	1.22
$0 - \theta_2$	-0.15	1.77

The higher educated have, on average, a larger tendency to underpredict and a smaller tendency to overpredict their future income change than the lower educated. Since we allow for macro-economic shocks – which are assumed to be independent of education level – we cannot unambiguously conclude whether the high educated have rational expectations and the lower educated tend to overpredict, or whether the low educated have rational expectations while the high educated tend to underpredict. The tables in Section 3, however, suggest that the latter is more likely than the former.

A similar conclusion holds for heads of households who receive a disability benefit. Compared to employed heads of household, they have a larger tendency to underpredict their future income change. The reason may be the ongoing public debate on reorganizing the disability benefit system in the Netherlands, which has led to considerable concern among the recipients. While the system has been adjusted, the income reductions of the disabled have not been as large as may have been expected. Moreover, the number of people on disability benefits has not fallen as much as the government had hoped, and this has resulted in new plans for further reorganizations.

In spite of the fact that the restricted model is rejected, the estimates in Table A3 which impose the REH restrictions contain some interesting results. First, the parameter m_3^p is not significantly different from 1. Thus there is no evidence that respondents use different thresholds for predictions and outcomes when they distinguish between no change and an income fall or an income rise. But of course it has to be admitted that this can only be investigated to a limited extent, due to the normalizations we have had to impose.

Second, the predicted macroeconomic effects ν_t are all smaller than the realized effects λ_{t+1} for the same time period. This result remains the same if we impose $m_3^p = 1$,and is therefore not due to the chosen normalization. If people had rational expectations and use the same category bounds for predictions and realizations, this would imply that all macroeconomic shocks are positive. This result therefore corresponds to the result found using the nonparametric tests.

Testing Adaptive and Naive Expectations

Table 4 immediately shows that many parameters in γ_1 are significant, and that the sum of θ_1 and θ_2 is much smaller than 1. Thus many of the restrictions on the parameters under adaptive expectations (given by (7)) are separately rejected, and a formal test on joint significance confirms that AEH is rejected. Since naive expectations are a special case of adaptive expectations, it should not come as a surprise that the hypothesis of naive expectations (NEH, restrictions (8)) is also rejected. Thus respondents' income change expectations are neither rational, nor adaptive or naive.

Some Probabilities of Predictions and Realizations

To obtain more insight in the results obtained with the general (unrestricted) model, we have computed some probabilities of predicted and realized income changes for some reference respondents. To do this, we have to give a stronger interpretation of the latent variables underlying the predictions and realizations. We assume that they can be interpreted as the underlying change on a continuous scale. Thus a positive value means a positive change and a negative value means a negative change, an assumption which seems reasonable given that in the general model, the bounds for the no change category are normalized to -1 and 1. Moreover, we interpret the probabilities that $y^*_{t+1} < p^*_t$ or $y^*_{t+1} > p^*_t$ as the probabilities that the realized income change is smaller or larger than the predicted change. This seems a plausible assumption given that the normalizations on the bounds are identical in both equations.

We consider male heads of household of two different education levels, the lowest and the highest level. Both have average age (46.3 years), are employees, are the only earner in their families, and have zero predicted and experienced income change in the previous period ($y^*_t = 0$ and $p^*_{t-1} = 0$). Individual effects are also set to zero. Without imposing REH, we cannot disentangle macro-economic shocks from prediction errors, and we therefore compare predictions and realizations including the macro-economic shocks, i.e. we incorporate the estimated time dummies in both equations in the computations. We consider two pairs of years: 1993-1994, for which Table A3 suggests that the macroeconomic shock is relatively small (cf. the time dummies in Table A3), and 1989-1990 for which the macroeconomic shock is much larger.

The first two rows in Table 6 compare the probability that the underlying latent variables are negative, i.e. that an income fall would be predicted or experienced on a continuous scale. As expected from the estimates in Table 4, both the probability that an income fall is predicted and the probability that an income fall is realized fall with education level. The difference is stronger for the realization than for the prediction. For

1993-1994, the probabilities of predicting and experiencing an income fall are not very different for the low educated, but for the high educated, an income fall is less common than the predictions would suggest. For 1989-1990, the actual income change tends to be better than the prediction for the lower educated, and the difference for the higher educated is even larger. This illustrates the result in Table 5 that the higher educated have a larger tendency to underpredict than the lower educated. It also confirms that in 1989-1990, the unanticipated macro-economic income shock was much larger than in 1993-1994.

The third row gives the probability that the realized continuously measured change exceeds the predicted continuously measured change. Under REH and without macro-economic shocks, this probability should be 0.5. It is always larger than that. Again, the high probabilities for the reference respondent with university level illustrate their relative pessimism, and the high probabilities for 1989-1990 suggest a positive macro-economic shock in that time period.

The fourth and fifth row of the table refer to the probabilities that the respondents *report* that they expect their income to fall (or to fall strongly), and *report* that their income has fallen (or has fallen strongly). These differ from the first two rows, since many respondents who predict or experience a only small negative change on the continuous scale, will report no change on the discrete scale. In other words, an income fall is reported only if prediction or realization are lower than some negative threshold, normalized to -1. Since the realizations have larger standard deviation than the predictions, this threshold is more important for the predictions than for the realizations. This explains why in 1993-1994, the probability that a realized income fall is reported, exceeds the probability that an income fall is predicted. The relative differences between years and education levels, remain the same as in the top rows.

Rows six and seven of Table 6 present the probabilities that a predicted and realized income rise are reported. The result is in line with what we already saw. For both years and both education levels, we find much larger probabilities that respondents ex post report an income rise than that respondents report ex ante that they expect their income to rise. This is partly due to the larger dispersion in the realizations, and partly to underpredicting. Differences between education levels and years lead to the same conclusions as in the remainder of the table.

Table 6. Probabilities based upon the estimates in Table 4. Bootstrapped standard errors are in parentheses.

probability	low educated t=1989		low educated t=1993		high educated t=1989		high educated t=1993	
$P(p_t^* < 0)$	0.50	(0.023)	0.55	(0.016)	0.46	(0.033)	0.51	(0.026)
$P(y_{t+1}^* < 0)$	0.30	(0.011)	0.49	(0.011)	0.24	(0.012)	0.41	(0.014)
$P(p_t^* < y_{t+1}^*)$	0.69	(0.018)	0.54	(0.015)	0.73	(0.023)	0.59	(0.022)
$P(p_t^* < m_2^p)$	0.14	(0.020)	0.17	(0.017)	0.12	(0.023)	0.15	(0.022)
$P(y_{t+1}^* < m_2^y)$	0.10	(0.006)	0.22	(0.008)	0.07	(0.006)	0.16	(0.009)
$P(p_t^* > m_3^p)$	0.14	(0.008)	0.12	(0.007)	0.16	(0.014)	0.13	(0.010)
$P(y_{t+1}^* > m_3^y)$	0.40	(0.011)	0.23	(0.008)	0.48	(0.015)	0.30	(0.011)

6 Conclusions

Using panel data on expectations and realizations of income changes, we have investigated whether heads of household have rational expectations. First, we have used the nonparametric framework of Manski (1990) to test the best case scenario of rational expectations and absence of macro-economic shocks, combined with two different assumptions on which location measure of their income change distribution respondents use to form their predictions. Both lead to the conclusion that the best case scenario is rejected for each of the ten combinations of years we consider, since too many people who expect an income fall experience no change.

Next, we have formulated a bivariate dynamic latent variable model for predictions and realizations of income changes. The model is consistent with the Manski (1990) framework combined with the notion that people's predictions reflect the mean or median of their subjective income change distribution, and extends models used by Nerlove and Schuermann (1995, 1997) for testing REH and AEH of businesses. Unlike the earlier models, our model can distinguish between macro-economic shocks and violations of rational expectations. Our main conclusion here is that REH is rejected under various assumptions on the macro-economic shocks, even if these macro-economic shocks are allowed to be correlated to household characteristics and income changes in the past.

Our results are based upon eleven years of data for one country only. Obviously, whether the results we find are specific to the country and the time period we consider remains to be seen. Still, our results suggest that alternative theories of expectations formation are needed to explain our data. This remains the challenge for future research.

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Appendix

Table A1. Definitions of exogenous variables

gender	gender head of household: 1 = male; 2 = female. If husband and wife are present, the husband is by definition head of household.
age/10	age head of household in tens of years.

Education level head of household

reference category: primary education only.

d_edu2	1 if lower vocational training; 0 otherwise.
d_edu3	1 if intermediate vocational training or highschool; 0 otherwise.
d_edu4	1 if higher vocational training; 0 otherwise.
d_edu5	1 if university degree; 0 otherwise.

Labour market status head of household

Reference category: employee.

d_unem	1 if unemployed; 0 otherwise.
d_ret	1 if retired; 0 otherwise.
d_dis	1 if disabled; 0 otherwise.

d_two	1 two-earner household; 0 otherwise.

Table A2. Estimates of initial condition equations in unrestricted model

Realization (y)			Prediction (p)		
variable	estimate	t-value	variable	estimate	t-value
constant_0	1.97	10.08	constant_0	0.78	3.22
gender_0	-0.13	-2.43	gender_0	-0.090	-2.25
$\text{age}/10_0$	-0.59	-7.06	$\text{age}/10_0$	-0.26	-2.93
$(\text{age}/10)^2_0$	0.043	4.33	$(\text{age}/10)^2_0$	0.019	2.16
d_edu2_0	0.078	1.24	d_edu2_0	0.0090	0.17
d_edu3_0	0.24	4.21	d_edu3_0	0.040	0.77
d_edu4_0	0.39	5.78	d_edu4_0	0.12	1.76
d_edu5_0	0.48	5.03	d_edu5_0	0.17	1.94
d_unem_0	-0.48	-5.28	d_unem_0	-0.21	-2.86
d_ret_0	0.053	0.52	d_ret_0	-0.069	-0.90
d_dis_0	-0.84	-10.31	d_dis_0	-0.33	-3.63
d_two_0	-0.10	-2.38	d_two_0	-0.067	-2.04
			θ_0	0.44	4.62
$\sigma_{\epsilon,0}$	1.41	85.82	$\sigma_{\omega,0}$	1.03	27.46
$\sigma_{\epsilon_1,\epsilon_0}$	-0.40	-6.97	$\sigma_{\omega_1,\omega_0}$	-0.10	-1.87
$\sigma_{\epsilon_t,\epsilon_0}$	0.059	4.22	$\sigma_{\omega_t,\omega_0}$	0.023	2.24
$\sigma_{\epsilon_0,\omega_0}$	-0.38	-2.04			
$\sigma_{\epsilon_1,\omega_0}$	0.45	10.38			
$\sigma_{\omega_1,\epsilon_0}$	0.038	1.30			
$\sigma_{\epsilon_t,\omega_0}$	-0.0031	-0.28			
$\sigma_{\omega_t,\epsilon_0}$	0.053	3.65			

Table A3. Estimates restricted model (restrictions: $\beta_1 = \gamma_1, \theta_1 = \rho, \theta_2 = 0$)

Realization (y)			Prediction (p)		
variable	estimate	t-value	variable	estimate	t-value
constant$_0$	1.94	9.98	constant$_0$	0.90	3.52
gender$_0$	-0.13	-2.51	gender$_0$	-0.097	-2.37
age/10$_0$	-0.58	-6.96	age/10$_0$	-0.28	-3.07
$(\text{age}/10)_0^2$	0.042	4.24	$(\text{age}/10)_0^2$	0.020	2.22
d_edu2$_0$	0.076	1.22	d_edu2$_0$	0.018	0.33
d_edu3$_0$	0.24	4.25	d_edu3$_0$	0.039	0.71
d_edu4$_0$	0.40	6.00	d_edu4$_0$	0.11	1.60
d_edu5$_0$	0.50	5.25	d_edu5$_0$	0.16	1.78
d_unem$_0$	-0.48	-5.22	d_unem$_0$	-0.24	-3.22
d_ret$_0$	0.048	0.47	d_ret$_0$	-0.056	-0.71
d_dis$_0$	-0.83	-10.15	d_dis$_0$	-0.37	-3.85
d_two$_0$	-0.10	-2.40	d_two$_0$	-0.071	-2.08
gender	-0.14	-8.57			
age/10	-0.28	-10.04			
$(\text{age}/10)^2$	0.019	6.42			
d_edu2	0.019	0.94			
d_edu3	0.067	3.71			
d_edu4	0.15	6.71			
d_edu5	0.18	6.43			
d_unem	-0.17	-5.23			
d_ret	-0.063	-2.37			
d_dis	-0.17	-6.77			
d_two	-0.077	-5.88			
ρ	0.45	20.52	θ_0	0.45	4.44
λ_{1986}	1.33	16.48	ν_{1986}	0.94	9.47
λ_{1987}	1.21	14.62	ν_{1987}	0.99	9.93
λ_{1988}	1.17	14.33	ν_{1988}	1.05	10.47
λ_{1989}	1.43	17.28	ν_{1989}	1.02	9.82
λ_{1990}	1.68	19.78	ν_{1990}	0.94	8.74
λ_{1991}	1.24	14.55	ν_{1991}	1.12	10.41
λ_{1992}	1.23	14.59	ν_{1992}	1.13	10.69
λ_{1993}	1.26	15.17	ν_{1993}	0.94	9.42
λ_{1994}	1.05	12.94			

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Table A3, continued					
variable	estimate	t-value	variable	estimate	t-value
m_1^y	-1.86	-122.32	m_1^p	-2.06	-49.77
m_2^y	-1		m_2^p	-1	
m_3^y	1		m_3^p	1.08	14.94
m_4^y	2.62	142.43	m_4^p	2.73	21.11
$\sigma_{\epsilon,0}$	1.41	86.12	$\sigma_{\omega,0}$	1.06	20.59
σ_{ϵ}	1.33	110.58	σ_{ω}	0.99	32.60
σ_{α_y}	0.056	1.14	σ_{α_p}	0.25	11.56
$\sigma_{\epsilon_1,\epsilon_0}$	-0.43	-8.58	$\sigma_{\omega_1,\omega_0}$	-0.0067	-0.41
$\sigma_{\epsilon_t,\epsilon_0}$	0.053	4.01	$\sigma_{\omega_t,\omega_0}$	0.030	2.36
$\sigma_{\epsilon_t,\epsilon_{t-1}}$	-0.48	-13.18	$\sigma_{\omega_t,\omega_{t-1}}$	0.0005	0.04
$\sigma_{\alpha_y,\alpha_p}$	-0.0011	-0.20			
$\sigma_{\epsilon_0,\omega_0}$	-0.37	-1.90			
$\sigma_{\epsilon_t,\omega_t}$	-0.50	-14.97			
$\sigma_{\epsilon_1,\omega_0}$	0.46	9.28			
$\sigma_{\omega_1,\epsilon_0}$	0.066	2.80			
$\sigma_{\epsilon_t,\omega_0}$	-0.0066	-0.61			
$\sigma_{\omega_t,\epsilon_0}$	0.063	4.14			
$\sigma_{\epsilon_t,\omega_{t-1}}$	0.45	16.26			
$\sigma_{\omega_t,\epsilon_{t-1}}$	-0.032	-2.47			
log likelihood: -59429 (number of observations = 6408)					